An Empirical Research of Seasonality in Chinese Stock Markets

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Abstract. Due to the expansion of the Chinese financial market, the characteristics and influencing factors of the Chinese stock market, including seasonality, have received increasing attention from researchers. This article covers the researchers' use of several techniques to examine the stock market's seasonality at various temporal and geographic scales, and then investigates the seasonality in the Chinese stock market. In order to focus on relatively stable stock market data, this article selected A-share data from January 1, 2011, to December 31, 2022 in the CSMAR database. The paper firstly used descriptive statistical methods to study the relationship between monthly average return rate over the entire study period and the average return rate of all data, as well as the relationship between the monthly returns and their volatility. To study the seasonality and volatility, this paper used ARIMA(1,1,1)-GARCH(1,1) model, which has good data match. The results of running these models show that there is a monthly effect in the Chinese market caused by Lunar New Year. Chinese stock markets do not have half-year effect. These results indicate that cultural and structural factors are important in shaping the seasonality of the Chinese stock market. Even considering the associated risks and uncertainties, trading strategies regarding seasonality in the stock market may still bring attractive returns.

Keywords: Seasonality, Volatility, Chinese Stock Market.

1 Introduction

China's stock market is playing an ever-increasing role in the world economy as the second-largest in the globe. With the growth of the Chinese economy and the gradual opening up of its financial markets, China's stock market is attracting more and more attention from domestic and international investors. A shares and B shares are separated on the Chinese stock market. B-shares are primarily available to overseas investors whereas A-shares are traded in local markets and are pegged to the Chinese yuan. In recent years, China's stock market has experienced tremendous volatility. These fluctuations have been attributed to various factors including regulatory policies, economic conditions and changes in investor sentiment. However, one factor that is thought to have contributed to the creation of these fluctuations is the seasonal pattern of the stock market. Some studies have found that Chinese stock market activity tends

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to be higher in the first and fourth quarters of the year. Other research have found that a few certain holidays and festivals significantly affect stock market activity. Changes in the seasonal patterns of the Chinese stock market have become an important topic of research. Research into the causes and effects of these patterns could provide valuable insights into the dynamics of the Chinese stock market and the value of the wider global economy. There has been a significant amount of research into seasonal patterns in equity markets around the world, including in China. However, these studies have concentrated on identifying and describing these patterns rather than exploring their underlying causes and effects in depth. There is therefore a need to further examine the cultural and structural factors that contribute to the seasonal patterns in the Chinese equity market in order to gain a deeper understanding of the dynamics of the Chinese equity market and to develop more informed investment and regulatory strategies. The seasonal patterns of the Chinese equity market have important implications for investors and regulators alike. For investors, understanding these patterns can provide more valuable insights into when to buy and sell stocks. For regulators, the seasonal patterns of stock market activity present challenges in maintaining market stability and transparency. Both cultural and seasonal factors have an important impact on the Chinese stock market. The remainder of the essay is structured as follows. Literature reviews are included in Section 2. Data and sample creation are described in Section 3. The empirical findings and robustness analyses are presented in Section 4. Section 5 concludes.

2 Literature Review

The stock market exhibits seasonality, which indicates the market's inefficiency and suggests the prospect of arbitrage possibilities. The internal workings of seasonality in the stock market and its particular performance have been thoroughly studied by researchers. There is a phenomena known as the day of the week effect, which causes stock returns to vary on average depending on the day of the week. The average return rate on Monday is low, which may be due to investors being pessimistic about speculative stocks on Monday and the returns to the quality-minus-junk factor [1].

Harshita et al. reported that the return in November is highest as compared to the other months in India. The main reason for higher returns in November is the cultural factor like Diwali and high liquidity among the investors. Different assets have different sensitivities to investors' preferences and beliefs, and this difference can explain seasonal phenomena in the stock market [2]. Investors have the option of purchasing equities with high or low mood beta depending on the month's mood [3]. The trading method created in accordance with the conclusion offered a sizable excess return [4]. Research on stocks with lottery characteristics found consistency between stock seasonality and investor speculation [5]. Researchers have further backed the tax-loss selling theory of the January effect with the permanent earnings valuation model [6].

Researchers also examined the stock market's seasonality at various junctures and regional levels [7]. Research that uses the GARCH model to study stock market data from emerging countries such as India and Indonesia has also shown that most emerging country markets have monthly and asymmetric effects [8]. Researchers used natural language processing to study the data on China's stock market and found that the weekend information had less interference with investor sentiment, which led to an increase in investor sentiment during the holiday [9]. The dominant position of individual investors' shareholding contributes to the overall changes in the stock market, and cultural factors such as different media environments can also affect investor sentiment. In the past, academics have frequently used the OLS method to investigate the seasonality of stock return. The error term, however, might be autocorrelated, resulting in false inference. Furthermore, OLS makes the unpractical assumption that the error variance is constant, despite the extensive research supporting its time dependency. In order to manage heteroskedasticity and capture the volatility clustering in stock returns, GARCH models have been applied in numerous recent research [10].

3 Methodology

3.1 Data Selection

Our data comes from the CSMAR database, and we have selected daily stock returns for the Shanghai A-share market with consideration of reinvested cash dividends from January 1, 2011, to December 31, 2022, as the research object. The data set excluded stocks with the symbol ST, ST*, and missing data. The reason for selecting this period of data as the research object rather than data from earlier periods is that, firstly, the Chinese stock market was not mature before 1997, and was greatly influenced by human factors or policy decisions. It was only after the introduction of the limit on price changes on December 16, 1996 that the Chinese stock market entered a relatively stable period. In addition, from April 2005, China began to carry out share reform, and many companies were suspended due to share reform, causing interruptions in the returns of individual stocks. Moreover, the price behavior of listed companies may have changed compared to before share reform. These enormous fluctuations in returns caused by these factors may have affected our research analysis, so they were not adopted.

3.2 Modelling

This paper first used descriptive statistical methods to observe the relationship between the average return rate for each month over the entire study period and the average return rate for all data, as well as the relationship between the monthly returns and their volatility, in order to make a preliminary determination of whether the Chinese stock market has a monthly effect.

It then used modeling to investigate if the Chinese stock market exhibits a month-of-the-year influence. It will use an ARIMA(p, d, q)-GARCH(m, n) model for empirical analysis. In this model, the ARIMA model deals with the trend and seasonality of the monthly average returns time series, while the GARCH model deals with the heteroscedasticity of the residuals, thereby better reflecting the changing volatility of the financial market. Moreover, building a GARCH model can improve the fitting and prediction accuracy of the ARIMA model. The GARCH model assumes that the variance is a weighted sum of past forecast errors, meaning that it is conditionally heteroscedastic. Modeling the residual sequence using the GARCH model can provide better modeling of the residual sequence. After processing the data, we used the unit root test to verify that the data is non-stationary, but after differencing the data, we found that the sequence became stationary. At the same time, the test statistic is significantly lower than the critical value, further supporting this conclusion. Therefore, the sequence needs to be differenced or otherwise transformed to stationary before applying ARMA or other time series analysis methods for modeling and forecasting. Consequently, we used the ARIMA model for research, which first takes the difference of the data to obtain a stationary sequence, and then carries out ARMA regression on the stationary sequence.

This paper has tested different combinations of p, d, q, m, and n for this model, and found that the ARIMA(1,1,1)-GARCH(1,1) model has relatively small AIC, SC, and MSE values in evaluating the model fitting effect. Therefore, we have selected this model to study the monthly effect, as follows:

$$R_t = \alpha + \Phi R_{t-1} + \theta \varepsilon_{t-1} + \beta X_t + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \omega + \mu \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 \tag{2}$$

Where R_t represents the rate of return at time t, R_{t-1} represents the rate of return at the previous time point, ε represents the error term, and X_t represents the dummy variable for months. When X_t= 1 represents the month under study, and when X_t= 0 represents other months. ε_t is the error term, and α, ϕ, θ, β, μ, γ, ω is the model coefficient. When β is significantly different from 0, it can be shown that there is a month effect in the A-share market in China.

4 Empirical Results

Fig. 1 displays the average return rate for each month over the entire study period, with the red dotted line indicating the average return rate for all data. It can be observed that the return rates in February and March are much higher than the average, while the return rates in January and June are much lower than the average. This suggests that February and March may have significant positive monthly effects, while January and June have significant negative monthly effects. Fig. 2 shows that there is no significant correlation between the average return rate for each month and its volatility.

Fig. 1. Average monthly returns with mean returns.

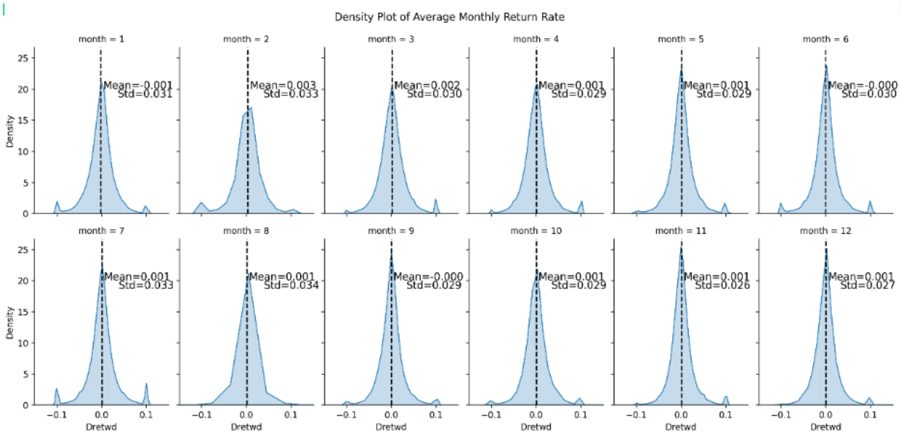

Fig. 2. Density plot of average monthly return.

Table 1 and Table 2 show that the impact of dummy variables is relatively significant in January, February, June, and December, among which January, February, and June have the most significant impact.

Table 1. Results of GARCH model.

Month	ω	μ	γ
January	0.006177	0.334168**	0.536302***
	(1.427534)	(2.233508)	(3.910029)
February	0.005650	0.269635**	0.597541***
	(1.503586)	(2.379591)	(6.832345)
March	0.006327*	0.347829**	0.526856***
	(1.742363)	(2.412969)	(5.018558)
April	0.006557*	0.341973**	0.525281***
	(1.755421)	(2.372999)	(4.895717)

Table 2. Results of GARCH model. (continue)

May	0.006061*	0.349783**	0.532911***
	(1.69667)	(2.394499)	(4.942890)
June	0.008088**	0.271793**	0.536486***
	(2.090538)	(2.217922)	(5.944660)
July	0.006180*	0.344941**	0.533760***
	(1.713133)	(2.365212)	(5.019863)
August	0.005687	0.369098**	0.530174***
	(1.617760)	(2.375367)	(5.200658)
September	0.006307*	0.326681**	0.543820***
	(1.652896)	(2.351805)	(4.806129)
October	0.006748*	0.328435**	0.531767***
	(1.840322)	(2.238751)	(4.665165)
November	0.006016	0.302863**	0.569237***
	(1.476526)	(2.258729)	(4.986371)
December	0.006384*	0.324595**	0.544548***
	(1.761030)	(2.074348)	(4.997016)

Table 3. Results of ARIMA model.

Month	Φ	θ	β	ε
January	-0.533125662***	-0.999706	-0.1249***	0.038729
	(-8.40741)	(-0.16279)	(-2.94836)	(0.16360)
February	-0.52433912***	-0.999317	0.1193***	0.03892
	(-8.93579)	(-0.43230)	(2.65872)	(0.43765)
March	-0.558763041***	-0.999795	0.0702	0.040037
	(-8.82101)	(-0.11606)	(1.19291)	(0.11651)
April	-0.533185478***	-0.998725	0.0252	0.040613
	(-9.13483)	(-0.72954)	(0.41717)	(0.74368)
May	-0.535237922***	-0.999225	-0.0215	0.040606
	(-9.25251)	(-0.45426)	(-0.39373)	(0.45979)
June	-0.546061774***	-0.999336	-0.0976*	0.039452
	(-9.49076)	(-0.40388)	(-1.67488)	(0.40803)
July	-0.53301573***	-0.999015	0.0062	0.040784
	(-9.08344)	(-0.57280)	(0.10296)	(0.58189)
August	-0.53361774***	-0.999193	0.0359	0.040498
	(-9.04702)	(-0.46689)	(0.56669)	(0.47285)
September	-0.531785932***	-0.999196	-0.0306	0.040586
	(-9.06521)	(-0.45816)	(-0.43725)	(0.46552)
October	-0.535445585***	-0.998843	0.0346	0.040546
	(-9.23777)	(-0.68846)	(0.74979)	(0.70123)
November	-0.540119612***	-0.999033	0.0607	0.040216
	(-9.39516)	(-0.54797)	(1.05076)	(0.55973)
December	-0.551413732***	-0.998941	-0.0730	0.039949
	(-9.69172)	(-0.60914)	(-1.59463)	(0.61849)

Table 3 shows the coefficients and error terms of the ARIMA model. The dummy variable's coefficients are significantly negative in January and June. And the dummy variable's coefficient is significantly positive in February. The coefficients of other months are not very significant. This result suggests that the Chinese market has a monthly effect, and its period is different from foreign markets. This has something to do with China's special traditions which contribute to the holiday effect. The reason behind the positive result in February is that the CNY, based on the lunar calendar, making the 'turn of the year' in China occur in February instead of January. And the explanation for the negative effects in June is that China's stock markets don't have half-year effect while foreign stock markets tend to have a strong one. Seeing from the table, all coefficients Φ are significantly negative. All of these consequences can be attributable to the distinctive characteristics of the Chinese stock market, where structural and cultural influences are both significant.

With all the effects and investment strategies taken into account, we find that the A stock markets are likely to be more profitable after adjusting for risk differences. The returns from some of these investment strategies remain attractive. This indicates that although seasonality bring about more uncertainties and abnormality in China's stock markets, we can still draw even more profits as long as we make the investing choice in the right period. However, from our empirical results, we can see that despite the fact that our investment profits differ with the consideration of the month effects, the differences are not very manifest.

5 Conclusion

The study has important implications for both investors and regulators. For investors, the findings highlight the importance of understanding the seasonal patterns of the Chinese equity market and the risks associated with the potential opportunities associated with these patterns. In terms of possible investment strategies, A-shares tend to be more profitable based on known characteristics. Even when considering the different transaction costs in the A-share and B-share markets, some investment strategies still offer attractive returns. For regulators, targeted policies and interventions are needed to mitigate the potential risks associated with seasonal patterns of stock market activity. While the study provides valuable insights into the seasonal patterns of the Chinese stock market, the study still has limitations. The analysis is based on a relatively short period of data, with longer trends and patterns likely to emerge over time. It is worth noting that the Chinese government has been taking steps to deregulate A and B shares in recent years, which may lead to further changes in the A and B share landscape. The impact of cultural and structural factors on the pricing of the Chinese equity market may change accordingly, which is subject to further study. It is important to note that while external capital from looser policies has undoubtedly had an impact on Chinese A and B shares, it is unlikely that the impact of cultural and structural factors on Chinese equity markets will be eliminated. These factors remain an important part of the market ecosystem and at some point will still have a big impact on market dynamics.

References

1. Chiah, M., & Zhong, A.: Day-of-the-week effect in anomaly returns: International evidence. Economics Letters 182, 90–92 (2019).
2. Harshita, Singh, S., & Yadav, S. S.: Calendar anomaly: unique evidence from the Indian stock market. Journal of Advances in Management Research 15(1), 87–108 (2017).
3. Hirshleifer, D., Jiang, D., & Meng, Y.: Mood beta and seasonalities in stock returns. Journal of Financial Economics 137(1), 272–295 (2020).
4. Wen, F., Liu, Z., Cao, J., Zhang, Y., & Yin, Z.: Mood seasonality: Evidence from the Chinese A-share market. Finance Research Letters 46, 102232 (2021).
5. Gould, J., Yang, J. W., Singh, R., & Yeo, B.: The seasonality of lottery-like stock returns. International Review of Economics & Finance 83, 383–400 (2022).
6. Easterday, K. E., & Sen, P. K.: Is the January effect rational? Insights from the accounting valuation model. The Quarterly Review of Economics and Finance (2016).
7. Mitchell, J. P., & Ong, L. L.: Seasonalities in China's Stock Markets: Cultural or Structural? IMF Working Paper 06(4), 1 (2006).
8. Aggarwal, K., & Jha, M. K.: Stock returns seasonality in emerging Asian markets. Asia-pacific Financial Markets (2022).
9. Liu, Q., Wang, X., & Du, Y.: The weekly cycle of investor sentiment and the holiday effect – An empirical study of Chinese stock market based on natural language processing. Heliyon 8(12),12646 (2022).
10. Chatzitzisi, E., Fountas, S., & Panagiotidis, T.: Another look at calendar anomalies. The Quarterly Review of Economics and Finance 80, 823–840 (2021).